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Deep Learning Models for Oil Spill Detection in Marine Settings: A Literature Review

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Abstract: *Oil spills in marine settings can be identified and tracked by remote sensing. The accuracy and effectiveness of oil spill detection using faraway sensing data have shown tremendous promise for deep learning (DL) algorithms, particularly deep neural networks (DNNs). In this literature review, we summarized the key DL models that have been used in oil spill detection, including CNN, RNN, DBN, AE, and GAN. We also discussed the different components and tasks involved in DL models, such as pooling layers, forward and backpropagation, and optimization of weights. Additionally, we present several case studies that have successfully applied DL approach in oil spill recognition, including the use of DBN to differentiate oil spills from lookalikes in SAR images, and the use of spatial-spectral jointed SAE to acquire and categorize oil slicks on the ocean surface using hyperspectral data. The findings from these studies demonstrate the potential of DL models to improve the accuracy and proficiency of oil spill detection using RS data.*

Keywords: *Deep Learning, Convolution Neural Network, Oil Spill Detection, Synthetic Aperture Radar Image, Deep Neural Networks, Remote Sensing*

1. INTRODUCTION

Oil spills are a major universal environmental concern, with significant impacts on plant and animal life, potentially leading to genetic mutations [1]. Oil spills can occur during various phases of oil production including drilling, production, and transportation. Transportation-related oil spills are particularly dangerous because they can occur in areas where people, animals, and farmlands are present, such as rivers, seas, mountains, and deserts.

To address the issue of oil spills in Nigeria, second largest oil-producing country in Africa, the federal government established the National Oil Spillage, Detection, and Response Agency and enacted several environmental protection laws [1]; [2]. NOSDRA enforces penalties for violations of these laws, as seen in the case of Mobil's oil Unlimited Company, Akwa Ibom terminal, Nigeria, which was fined for spill infringements of 2011 regulations [2].

In addition to legislative measures, various technological techniques such as optical techniques, visual spectrum, infrared, and satellite imaging. However, despite these efforts, the Niger Delta, which is one of Nigeria's most ecologically sensitive areas, has experienced significant environmental degradation owing to decades of oil drilling and extraction activities [3]; [4]; [5]; [6]. This area is home to various ecosystems, including mangrove swamps, freshwater marshes, and rain forests, and is the tenth largest wetland in Africa [5]. The discovery of crude oil in the area in 1956 by Shell British Petroleum led to the creation of numerous oil enterprises, with significant negative impacts on the local population and environment [7].

According to the Department of Petroleum Resources (DPR) records, there were 16,476 oil spills in the Niger Delta area between 1976 and 2015, with nearly three million barrels spilled into the environment. Unluckily, more than seventy percent of the spilled oil did not recover, and sixty nine percent of the spills occurred offshore, while twenty five percent happened in swamps and six percent on land [8]. This region has become one of the five most seriously damaged ecosystems in the world due to unsustainable oil exploration [8].

Researchers have employed different methods, including boats, aircraft, and satellites, to distinguish and recognize oil spills. Aircrafts and satellites prepared with Synthetic Aperture Radar (SAR) and Real Aperture Radar (RAR) have remained the most practical means of monitoring sea-based oil contamination [9]. SAR and RAR are key instruments for obtaining images suitable for oil spill monitoring because they produce data independent of weather conditions and time of day [10].

To extract essential features from targeted objects in remotely sensed images, researchers use descriptor extraction, which is an important method in computer-vision technologies. Satellite images contain features, such as color, texture, shape, edges, and shadows. Feature models relating to a variety of characteristics such as color, texture, edges, shapes, and intensity are extracted using various techniques to extract the desired elements from satellite images [11].

Oil spills can be extracted from high-resolution satellite images using the correct approach, as satellite images clearly show the exact position and amount of oil leak spread. A robust approach for extracting oil spills from satellite images can be developed using colour and texture feature models.

In this review, a faster method with a high recognition capability for the early identification of oil leakage from high-resolution satellite images will be explored. Convolution neural networks (CNNs) have become a significant algorithm in signal processing, and improving the algorithm has been a subject of pronounced interest. The algorithm has evolved from a LeNet-style Model to AlexNet, where convolution operations are repetitive multiple times between max-pooling tasks; which makes the network learn richer descriptors at every spatial scale. The Visual Geometric Group (VGG) in 2014, introduced a new architecture called the Inception architecture, which was later improved to Inception V2 and then redefined as Inception V3. The inception module is a step from former VGG networks; that were earlier stacks of simple convolution layers [12].

2. LITERATURE REVIEW

This segment offers an overview and categorization of the related literature on oil spillage detection and monitoring, including traditional techniques and remote sensing methods. In the first subsection, the oil and oil spills are provided. The second subsection provides a review of Remotely Sensed Data, while the last subsection provides an approach to oil spill detection.

2.1 Review of Oil and Oil Spill

This subsection discusses the origin of oil and the harmful results of oil spills on the atmosphere and marine life, particularly in the Nigerian Niger Delta community.

Oil is a mixture of hydrocarbon molecules, which are the decomposed remains of sea plants and animals that have sunk to the Earth 's crust. These fossils have been converted into complex hydrocarbons known as petroleum during the last 600 million years under conditions of extreme pressure and temperature. Crude oil contains gas, naphtha, kerosene, light gas, and residuals that are harmful to the health of all living organisms when ingested [13]. Oil spills (a form of pollution) refer to the discharge of liquid petroleum hydrocarbons into the environment, particularly into marine ecology [14].

Oil spills in the sea pose a critical problem because of their detrimental effects on marine and coastal ecosystems. However, satellite imagery provides a cost-efficient and straightforward result for monitoring vast areas and identifying oil spills, thus offering several benefits to the classification system.

Although the Earth harbors vast oil and gas reserves beneath its surface, its release into the environment is a natural occurrence resulting from the corrosion and fissures of the Earth’s crust. Such incidents rarely cause any significant harm [15]. However, when third-party interference (TPI) causes oil spills, it can have serious consequences on marine ecosystems. The consequences of oil spills have recently garnered significant attention, posing a variety of issues for both the environment and humans. Oil spills are a primary contributor to marine pollution and a significant threat to marine life. Consequently, maritime inspectors have made oil detection a crucial task [16].

The Niger Delta community in Nigeria suffers from severe economic and ecological consequences due to oil spills [17], which has sparked political and media debates about how the government should respond to such incidents and what measures could be taken to prevent them. Several studies have focused on developing automated or semi-automated methods to distinguish oil spills [18]; [19]; [20]; [9]; [19]. Remote sensing and marine SAR datasets have been used to identify oil spill patches and differentiate them from lookalikes [21]. However, radar images may be distorted by various look-alikes, and eliminating them has been the subject of many investigations [21]. SAR image processing typically involves evaluating image quality and eliminating noise and speckles [21]. Speckles are a specific type of granular noise caused by interference of the image signal, and if present, they may hinder further processing.

Oil often displays a constant texture that differs from the coarser texture of the sea. Therefore, shape analysis can be used to locate areas containing black oil [21]; [10]. Intelligent systems have been developed to support image processing, resulting in numerous automated or semi-automated procedures that are capable of identifying oil slicks in radar images.

2.2 Review of Remotely Sensed Datasets

This subsection offers an overview of the use of active microwave sensors, such as SAR and SLAR, for oil spill detection and monitoring, highlighting the benefits and disadvantages of this technology and the impact of radiometric parameters on the attendance of oil spills in SAR images. This section also explores the potential of SAR technology for various other applications and its increasing affordability owing to lower-cost electronics. Finally, this section discusses recent advancements in the use of polarimetric images for oil pollution recognition using SAR imagery.

In recent decades, RS has developed an essential tool for distinguishing and observing oil spills, using images collected from the sensor systems. Active radars use their capacity to brighten the target and record reflected waves, whereas passive radars acquire naturally reflected solar radiation. Remote sensing approaches for detecting, monitoring, characterizing the type, and estimating the width of oil spills comprise detectible and infrared multispectral, hyperspectral, thermal, microwave, and laser fluoro sensors. However, each technique has its own advantages and disadvantages, making it challenging to obtain crucial data for efficient oil spill management from a single source [22]; [23]. Therefore, choosing the appropriate technique(s) often requires a compromise between the various options available.

Active microwave sensors, such as SAR and SLAR, are commonly used for oil spill recognition and observation because of their ability to collect data throughout the day and night beneath all-season circumstances and provide vast coverage [24]. SAR and SLAR transceiver reflected radio waves and record the reflection of the object exterior properties to create two-dimensional imageries of the sight as shown in Figure 2.1. The two systems used the same SAR technique and side-seeing image geometry. Literature has demonstrated the effectiveness of satellite-based SAR data for oil spill detection [25]; [26]. However, oil spills can easily be confused with other events that limit the scattering mechanism and cause SAR images to appear dark, such as natural surface films, internal waves, and ship wakes. Oil spills appear black in SAR images because they dampen small-scale sea surface capillaries and brief gravity waves.

Radiometric parameters of radar imaging, such as wavelength, frequency, and polarization, affect the appearance of oil spills in SAR images. The L-band (24 cm wavelength), C-band (six centimetre wavelength), and X-band (three centimetre wavelength) are commonly used in oil spill detection, with the C-band being the most frequently used [24]. SAR systems use different polarization techniques, such as single (HH or HV), dual (HH/HV or VV/VH), and quad (HH, HV, VH, and VV), which allow the extraction of unique information to identify and monitor oil spills. Sentinel-1 and Radarsat-2 provide dual-polarized SAR data in the form of HH+HV or VV+VH. However, certain characteristics of oil spills can only be detected with definite divergences, such as an oil spill being visible in the VV band of Sentinel-1 data but not the same as VH band [24].

2.2.1 Synthetic Aperture Radar Imaging

The launch of SEASAT in 1978 marked the beginning of a new era in ocean phenomenon research. SAR satellites have provided a wealth of information on various ocean occurrences such as surface waves, ocean currents, upwelling, sea ice, and rainfall [27]. In addition, SAR can detect human-made effects, such as offshore facilities, ship transits, and other ocean-related activities. SAR is an ideal sensor for detecting such events because it is sensitive to surface roughness variations of the order of the radar wavelength, ranging from 1 m to several centimetres. SAR is not affected by cloud cover and is not reliant on solar illumination. Furthermore, SAR offers control over characteristics, such as power, polarization, spatial resolution, frequency, phase, incidence angle, and swath width, all of which are crucial for the development and operation of a system for quantitative information extraction.

SAR technology has been utilized in numerous applications, such as providing geologists with terrain structural information for mineral development, environmentalists with oil spill borders on water, navigators with sea conditions and ice hazard maps, and military operations with targeting and reconnaissance information. SAR has several other potential applications, particularly in the civilian sector, which are yet to be fully explored. With the increasing affordability of SAR technology owing to lower-cost electronics, smaller-scale applications are becoming more feasible.

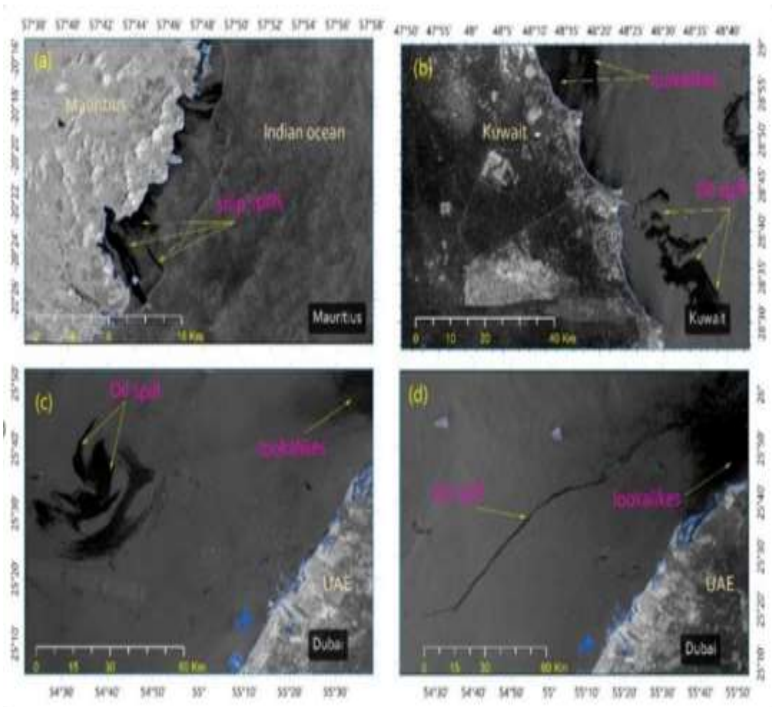

Figure 2.1: Sourced from [24], displays several oil spill events identified using microwave satellite images, including (a) a ship spill close to the Mauritius shore, (b) a vast oil slick off the Kuwait coast, (c) significant oil spills distinguished in the Arabian Gulf, and (d) an extensive oil spill near the UAE shore.

SAR sensors are active sensors capable of capturing imagery at any time, regardless of climate conditions. They can detect the geometry and structure of features such as terrain topography, surface cover thickness, and roughness. They can also detect wetness and vegetation.

2.2.2 SAR for oil spill monitoring

SAR technology has become a critical tool for creating synoptic charts of pragmatic scenes with high spatial tenacity and compressed return-to time, owing to its all-day and all-weather imaging capability. Traditionally, automated or semi-supervised classifiers have been applied to single-polarization SAR imagery for oil pollution detection by utilizing image-processing algorithms. However, in recent years, the increasing availability of complete and partial polarimetry data from various polarimetric SAR sensors has provided an unprecedented amount of physical information about the interaction between SAR illumination and observable regions. This has led to the development of a range of polarimetry techniques that exploit the deviation of oil-covered sea surfaces since Bragg scattering, which describes scattering from a fairly rough surface, as a slick-free sea. These polarimetric techniques had enabled the distinction between oil slicks and look-alikes, such as biogenic layers and low wind areas, thereby reducing or eliminating the want for trained workers and outside data (e.g., visual and scatter meter data) prerequisite for polarization SAR-based methods [28].

2.2.3 Single polarization SAR-based oil spill observation

Oil pollution monitoring is a critical application of remote sensing technologies, with SAR playing a vital role in creating synoptic charts of the detected region with sufficient altitudinal firmness and dense revisit time. SAR can operate almost independently of atmospheric conditions and cover vast aquatic zones in the event of oil grounds or significant oil slicks [29]; [30]. However, SAR-based oil spill observations have some limitations. Although SAR can generate synoptic maps of the observed region, it cannot provide accurate estimations of oil thickness [28]. Furthermore, SAR imaging can be affected by false positives such as ship wakes, biogenic surfactants, rain cells, oceanic currents, and upwelling zones, which can appear as black zones in SAR data [21]; [28].

Despite these limitations, SAR has proven to be effective for oil spill recognition owing to its extensive area coverage under any weather condition. The SAR algorithm for spill detection is an active microwave remote sensing device that records high spatial resolution using the relative motion between its antenna and the target. The steps involved in SAR-based oil spill observation include image acquisition, pre-processing, semantic segmentation, feature extraction, and classification [30].

In conclusion, remote sensing techniques, particularly active microwave sensors such as SAR and SLAR, have proven to be effective in recognizing oil spills because of their ability to collect data day and night under all-weather conditions and provide vast coverage. However, each technique has its own advantages and disadvantages, and choosing the appropriate technique(s) often requires a compromise between the various options obtainable. Imminent research should emphasis on exploring new applications of SAR technology and improving the dependability of oil spill recognition techniques.

2.3 Review of Approaches to Oil Spill Recognition

Oil spills are a major environmental issue wreaking havoc in marine ecosystems and coastal communities. Therefore, detecting and responding to oil spills as soon as possible is critical for effective mitigation efforts. In recent period, there had been a surge of attention in the usage of RS expertise for oil spill recognition. This section is the summary of the various approaches and techniques developed for oil spill detection as well as their benefits and drawbacks. The goal was to provide an overview of current oil spill detection methods and identify potential areas for future research.

Oil spills can be detected using different techniques, such as utilizing multi-polarization features or intensity SAR data with image processing techniques. CNNs have significantly advanced state-of-the-art image-recognition tasks and had been used in the recognition of oil spills. Traditional methods utilize region segmentation, slick feature extraction, and spot classification, whereas newer methods introduce pre-processing techniques and cascading neural networks. The use of pre-computed and manually created features has also been proposed for oil spill recognition in SAR imageries [31]; [32]; [33]. However, there are differences in the approaches used for SAR and SLAR images because of how the radar is mounted on satellites or aircraft, respectively [34]; [35]; [36].

2.3.1 Machine learning

Machine Learning (ML) is a subclass of Artificial Intelligence (AI) that assists machines to understand and performing tasks intelligently using command software. ML relies heavily on statistics and requires large databases to train algorithms [37]. ML provides a solution to the challenges in which an abstract understanding of a challenge remains insufficient and large amounts of observations are available. Owing to the obtainability of high-dimensional RS data and the complication of pattern classification assignments, ML approaches have been widely embraced for various Earth observation usage such as oceanography, likely catastrophes, agriculture, land use, and environmental monitoring [38]; [39]; [40]; [41]; [42]; [43]; [44]; [45].

In the domain of oil spill recognition, ML has been employed to develop various models using optical and synthetic aperture radar (SAR) images to offer efficient recognition systems to limit the effect of oil spills. ML strategies for oil slick recognition can be divided into two categories: conventional ML methods and deep learning (DL) approaches. The following sections discuss different modern ML models used for identifying, and recognizing oil spills using RS datasets.

2.3.2 Support vector machine (SVM)

Support Vector Machine (SVM) is a nonparametric overseen machine learning technique widely adopted in a range of remote sensing applications . SVMs seek to locate a separating hyperplane that provides the best parting of classes to reduce misclassifications and realize an acceptable simplification. The SVM is popularly used for oil spill classification because it can handle high-dimensional descriptors spaces and yield accurate identification results with a small amount of training examples [46]

Previous forms of SVM were designed for binary identification by determining the ideal hyperplane in linearly distinguishable situations, which were then used to overcome this constraint by charting the data into a high-dimensional descriptors space and building an enhanced separating hyperplane that dealt with nonlinear result surfaces . To reduce the computational rate of handling high-dimensional descriptor spaces, some filter functions such as direct, polynomial, switch, and Radial Basis Function (RBF) filters are used [46]. Radial basis function (RBF) and polynomial kernels are commonly used in oil spill investigations [47]; [48]; [19]. However, choosing the appropriate kernel type and parameter settings is crucial for an accurate classification. The SVM accuracies in oil spill investigations range from 71% to 97% [47]; [48]; [19].

2.3.3 Decision tree

Decision Tree (DT) is a nonparametric ML approach that uses a tree-like structure to recursively split the input dataset into branches of sub-datasets, each specified by a set of thresholds, descriptors, and a class tag [49]. DT is easy to train and interpret and can handle nonlinear connections between descriptor values from several ranges of values and classes. It is broadly used for the creation of rules for the classification of remotely sensed data using object-based recognition strategies.

The size of the decision tree is important for accurately representing feature vectors, and careful construction of a training dataset is essential for correctly distinguishing between oil spills and lookalikes [50]; [51]. However, DTs and fuzzy logic have been used less frequently than other traditional ML classifiers in oil spill research.

Several studies have likened the effectiveness of various classical ML models for oil spill recognition using the same image sources. For example, [52] used comprehensive and compact polarimetric SAR images to assess three frequently used overseen classifiers (ANN, MSVM, and ML). When adequate polarimetric information was obtained, the SVM followed by ANN outclassed ML. [53] used 47 ENVISAT Advanced Synthetic Aperture Radar (ASAR) images to test the performance of 428 classifiers from forty-one families, including groups, SVM, ANN, Bayesian, DT, RF, and many others, for oil spill identification.

2.3.4 Deep learning (DL)

Deep Learning (DL) procedures are a type of deep neural network (DNNs) that can automatically understand multifaceted discriminative descriptor from large amounts of data in a ranked method, stimulated by the arrangement and purpose of the human brain [54]. Unlike traditional machine-learning approaches, DL is entirely data-driven, allowing for the automatic mining of discriminative descriptors and eradicating the need for handcrafted descriptor extraction by professionals [55]. DL models have shown impressive capabilities and success in numerous fields, including RS and geoscience, by generalizing and automatically extracting information through multiple high-level layers of abstraction [56]; [57].

DL models can differ in their design, mechanisms, and assignment conditional on the neural network design used, such as CNN, RNN, AE, DBN, and GAN [58]. The depth of the neural network architecture is indicated by the amount of hidden layers, and DL models have more than one hidden layer [59]. Pooling layers, such as max and average pooling layers, are used to lower the dimensionality of feature maps and obtain features that are insensitive to the target location, thereby increasing the idea of mined descriptor and lowering the vector of the descriptor map input [60]; [61]. Several pooling methods like stochastic, spatial pyramid, and atrous spatial pyramid pooling have been applied in oil spill detection research [62]; [63].

The two main methods used for teaching and learning parameter weights in DL are forward and backpropagation, which involve the transfer of distinctive evidence and maximization of weights of trainable network parameters using backpropagation processes to reduce a predetermined cost function [64]. CNNs have been widely used as DL models for oil spill detection because of their excellent functionality in object recognition, image classification, and semantic segmentation, creating a probability map or segmentation for known classes from given data [56]; [57].

2.3.5 Recurrent neural network

According to [65], the recurrent neural network (RNN) is an improved version of the recurrent convolutional network that uses the same weight values repeatedly across the network's layers. RNNs can process various data types, including handwritten notes, images, acoustic signals, and fingerprints. The advantage of using RNNs is that their depth can be increased without adding additional layers or parameters. An RNN is the preferred network for solving such problems owing to its exceptional performance in natural language processing.

2.3.6 Deep belief network

A deep belief network (DBN) is a type of deep learning probabilistic model that has multiple hidden layers. It can perform various classification tasks either on its own or as a pretrainer for other deep learning networks to improve the initial weight values. By combining a DBN with a convolutional network, the time efficiency and network quality of the convolutional deep belief network can be enhanced by combining the benefits of both technologies [65].

2.3.6 Auto-encoder

The autoencoder (AE) architecture has been extensively researched, and various designs have been proposed, including multilayer, stacked (SAE), sparse, denoising, adversarial, and variation convolutional. Different types of AE have been discussed in the literature [66]; [67]. [26] used SAEs and DBNs to optimize SAR polarimetric features for unsupervised dimensionality reduction, which were then used as inputs in an overseen recognition process to detect marine oil slicks and biogenic lookalikes. The authors found that DL was inadequate for feature optimization in oil spill recognition, and the SAE and DBN techniques significantly increased classification accuracy with an inadequate number of models.

[19] did a spatial-spectral joint SAE (SSAE) to mine and categorize oil spills on the sea surface using hyperspectral data, and their model outperformed previous models, including SAE, SVM, and BPNN algorithms, by a significant margin. Two studies used diverse AE designs to section oil spills from the aerial SLAR datasets. [68] used SelAE with very deep lingering encoder-decoder networks to section oil slicks from SLAR data, while [69] developed a sectional AE with convolutional short-term memory to segregate oil spills and other maritime classes from the scanlines of SLAR aerial images.

2.3.7 Other deep learning models

Deep learning models are commonly used to detect oil spills using RS data. Convolutional neural networks (CNNs) and autoencoders (AEs) are popular models for this purpose, but other deep learning models, such as deep belief networks (DBN), recurrent neural networks (RNN), and generative adversarial networks (GAN), have also been used in a few studies [26].

[70] used a DBN method to differentiate oil slicks, mirror image, and water using the synthetic aperture radar (SAR) data from a limited sample space databank. In another study, [26] compared the accuracy of the SAE, DBN, and numerous conventional systems in detecting oil slicks from a small number of examples. Both the DBN and SAE outperformed the traditional machine-learning algorithms in terms of performance.

In supervised learning (SL), the goal is to generate outputs that are as similar as possible to the labels of the original images by deriving a model from sets of instances (input-output pairs) [71]. Artificial neural networks (ANNs), motivated by the human neural model, are the most widely used machine-learning approaches. ANNs consist of several computing elements called artificial neurons, which are interconnected with links having associated numerical weights [72]. The strength of neuron A on neuron B in two adjacent layers is expressed by the weight link between the two layers.

2.3.8 Deep neural network

A ((DNN) is an example of neural network design that contains multiple hidden layers. CNNs are among the most widely used DNN architectures and are highly effective in image classification and analysis [72].

2.3.9 Convolutional Neural Networks

CNN is a common and effective deep-learning model used for image recognition and classification [72]. CNNs are part of the Artificial Neural Network (ANN) family and were first introduced by Yann LeCun in 1988 [73]. They can perform various pattern recognition tasks, including image, face, handwriting, sound, digits, fruit, and oil spill detection [59]. CNNs consist of hundreds of hidden layers, each of which extracts different features from an image [74]. Some of the most popular CNN models include ResNet, AlexNet, GoogLeNet, and VGG, which differ in function, configuration, number of units, and depth.

Another key limitation of previous studies is their high computational complexity, which hinders real-time application. Advanced architectures such as U-Net, Transformer-based hybrids, and deep CNNs often require substantial processing power and time, making them impractical for real-time deployment in field-based or resource-constrained edge environments [75].

The CNN architecture involves passing images through a series of layers, including convolution, pooling, fully connected, and softmax layers, for feature extraction and object classification [76]. The weight-sharing network topology in CNNs allows for the direct feeding of images into a deep network, making them one of the most commonly used DL algorithms in image identification [73]. The fundamental structure of CNNs comprises convolutional layers, activation functions, pooling layers, and fully linked layers, which allow them to learn highly abstract descriptor from original features of images [77].

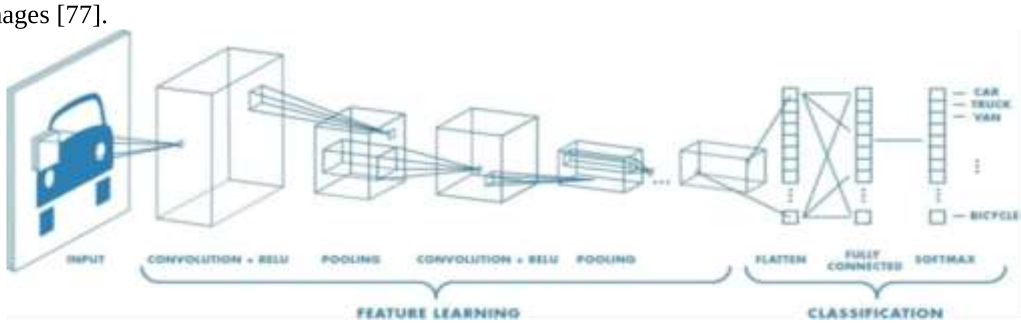

Figure 2.2a: Architecture of a convolutional neural network (CNN), sourced from (Source: Mahbub *et al.* 2018)

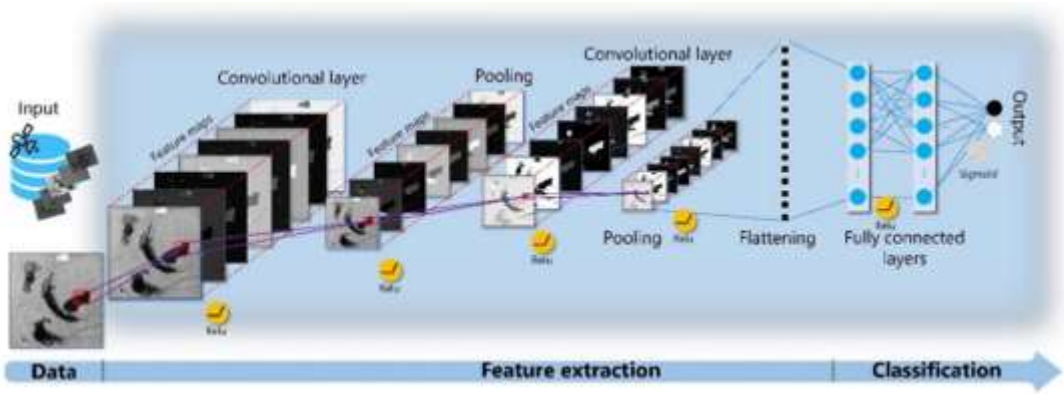

Figure 2.2b: The general framework of a convolutional neural network (CNN) (Source: [76]).

Convolutional layers are used to conduct descriptor extraction by applying many known convolutional filters to a portion of the input data. The output of each function is subjected to a nonlinear conversion via a residual linear unit, or others, such as, sigmoid, hyperbolic tangent, or softmax, to increase the nonlinear fitting capability of the CNNs. DL models such as CNNs can be specialized to have grid-like structures and scaled to very large sizes for improved learning capabilities [77].

ResNet and VGG are two popular CNN frameworks. ResNet is a deep neural network that utilizes skip connections across its layers to extend to deeper depths and detect objects more accurately than other standard deep neural networks. However, the VGG network excels in image-based classifications and won first place in the ILSVRC 2014 object localization challenge [78]. The selection of the CNN framework relies largely on the specific task and database.

2.3.10 Supervised learning

Supervised Learning (SL) is the most universally used machine-learning method for classification problems [37]. SL mimics the way humans learn, and involves selecting a problem and applying current knowledge to provide a solution. The solution was then compared with the known correct answer, and if it was incorrect, the knowledge was modified. This process was repeated for all other exercises. In the case of SL, the training data are an exercise problem, and the model is knowledge.

Classification is one of the most common applications of ML and SL is the preferred method for classification problems. Examples of classification problems include face recognition, where a face image is classified into one of the registered user models, and spam mail recognition, where mails are classified as either spam or regular. SL training data require input with the correct classes specified for each input. Neural Networks (NN) are among the models used to implement SL [37].

2.3.11 Unsupervised learning

Unsupervised Learning (USL) is a mode of machine learning that is used when there is an inadequate labelled pixel. In this scenario, each data point has simple features or covariates, but no associated labels. USL algorithms aim to discover significant pixels or fundamental characteristics in data, with examples including dimensionality reduction, density estimation, and clustering. By mimicking the human learning method of mimicry, the USL aims to educate the machine learning algorithm to create a concise internal illustration of the data. This representation can be useful in generative tasks in which the algorithm can produce creative content.

Unlike supervised learning, where data are labelled by a professional, unsupervised approaches display self-organization that acquires pixels as probability densities or a mixture of neural feature preferences. Other learning paradigms in the supervision spectrum include semi-supervised learning, in which a smaller subset of the data is labelled, and reinforcement learning, in which the computer is guided solely by a numerical accuracies score [79]

2.3.12 Reinforcement learning (RL)

Reinforcement Learning (RL) is a type of machine learning in which a neural network learns to perform tasks in dynamic and changing environments, such as in self-driving cars or learning robots. In RL, the learning system does not have any prior knowledge of the appropriate sequence of actions. The system is trained using a reward-based scheme, where it is rewarded for every correct decision and penalized for every incorrect action taken. Thus, RL is used to model dynamic orders of actions that are challenging to model using traditional machine-learning algorithms. RL is similar to how a mouse learns the structure of a maze, in which the system collects data through its actions. Successful training of RL methods is crucial for developing self-learning systems, and is often referred to as the holy grail of AI by researchers. Although the fields of neural networks and RL are independent, they complement each other well [37].

Several key methods for detecting oil spills, such as remote sensing and ML-based methodology, have been highlighted in a review of approaches to oil spill detection. Satellite imaging and aerial surveys are examples of remote sensing approaches, whereas machine learning-based approaches use artificial intelligence to analyse data and identify patterns that indicate the presence of an oil slick.

The complexity and variability of the marine environment, as well as the limited availability of data in some regions, are major challenges in detecting oil spills. To address these challenges, researchers have been working to increase the precision and dependability of existing methods, while also developing new techniques that can provide more comprehensive coverage of the marine environment.

Overall, this review emphasizes the importance of ongoing research and development in the field of oil slick detection, as well as the need for increased collaboration among researchers, industry stakeholders, and government agencies to develop more effective and long-term approaches to oil spill detection and response.

3. DISCUSSION

DL models have become increasingly popular for oil spill detection owing to their capacity to extract hidden representations and patterns from large datasets. CNNs have appeared as the most widely utilized DL design for oil slick recognition, owing to their excellent precision in object classification, image classification, and semantic segmentation. They can automatically learn discriminative features from image tiles and create a probability map or segmentation of predefined classes. Several pooling methods, such as max and average pooling layers, have been applied to increase the generalization of the extracted representations and reduce the input vector size. Table 3.1 summarized the strengths, weaknesses and other features of deep learning architectures.

Table 3.1: Comparison of deep learning architecture

Feature	Convolutional Neural Network	Recurrent Neural Network	Deep Belief Network	Autoencoder
Core Structure	Convolutional + pooling + fully connected layers	Sequential neurons with feedback loops (recurrent connections)	Stack of Restricted Boltzmann Machines (RBMs)	Encoder–decoder symmetric architecture
Input Type	Grid-like data (images, videos)	Sequential/time-series data (text, speech)	General-purpose; structured	General-purpose; usually vectorized data
Data Dependency	Spatial dependency	Temporal dependency	Hierarchical feature dependency	Feature representation and reconstruction
Parameter Sharing	Yes (convolution filters)	Yes (shared weights across time steps)	Limited (layer-wise pre-training)	Yes (shared weights between encoder/decoder sometimes)
Training Type	Supervised or self-supervised	Supervised (can be unsupervised via sequence prediction)	Unsupervised (layer-wise pretraining)	Unsupervised (reconstruction-based)
Memory Handling	No temporal memory	Has memory (captures past states)	No explicit memory	No temporal memory
Strengths	Excellent at spatial feature extraction; robust for visual tasks	Captures temporal/sequential dependencies	Learns hierarchical feature representations; good for pretraining	Learns compressed, denoised latent representations
Weaknesses	Poor at temporal modeling	Vanishing gradient in long sequences (fixed by LSTM/GRU)	Training is complex and computationally heavy	Poor generative ability (improved by Variational AE)
Output Type	Fixed-length feature maps or class labels	Sequential outputs (variable-length possible)	Feature embeddings or probabilities	Reconstructed data or latent features

RNNs have shown exceptional performance in natural language processing and can process various data types, including handwritten notes, images, acoustic signals, and fingerprints. However, their application in oil spill detection is limited owing to the lack of sequential information in the data. DBNs have multiple hidden layers and can perform various classification tasks either on their own or as pretrainers for other DL networks. They have been combined with CNNs to enhance the time efficiency and network quality of the convolutional belief belief network.

AEs have been extensively researched, and various designs have been proposed for feature extraction and dimensionality reduction, including multilayer, stacked, sparse, denoising, adversarial, variation convolutional, and vanilla AEs. They have shown promising results in oil spill detection, particularly when combined with DBNs for unsupervised dimensionality reduction. AE designs such as SSAE and SelAE have been used to extract and categorize oil slicks from the hyperspectral and SLAR data, respectively.

The limitations of DL models in oil spill detection include the need for large and high-quality datasets, potential for overfitting and model complexity, and lack of transparency and interpretability of the learned features. The performance of DL models can also be affected by the atmospheric and environmental conditions, sensor noise, and image resolution. Future research directions include the integration of DL models with physical models and other machine learning techniques, development of transfer learning and domain adaptation methods, improvement of data quality and preprocessing, and exploration of explainable AI techniques for model interpretability and transparency.

4. CONCLUSION

DL models have shown great potential for automatic feature extraction and classification in oil slick identification using remotely sensed data. CNNs, RNNs, DBNs, and AEs are among the most broadly utilized DL architectures in this field because to their advantages and limitations. The integration of DL models with physical models and other machine learning techniques, improvement in data quality and preprocessing, and exploration of explainable AI techniques are among the future research directions for increasing the sensitivity, precision, and efficiency of oil slick detection and monitoring.

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